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Spectral and thermal sensing for nitrogen and water status in rainfed and irrigated wheat environments

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Abstract Variable-rate technologies and site-specific crop nutrient management require real-time spatial information about the potential for response to in-season crop management interventions. Thermal and spectral properties of canopies can provide relevant information for non-destructive measurement of crop water and nitrogen stresses. In previous studies, foliage temperature was successfully estimated from canopy-scale (mixed foliage and soil) temperatures and the multispectral Canopy Chlorophyll Content Index (CCCI) was effective in measuring canopy-scale N status in rainfed wheat (*Triticum aestivum* L.) systems in Horsham, Victoria, Australia. In the present study, results showed that under irrigated wheat systems in Maricopa, Arizona, USA, the theoretical derivation of foliage temperature unmixing produced relationships similar to those in Horsham. Derivation of the CCCI led to an r^2 relationship with chlorophyll *a* of 0.53 after Zadoks stage 43. This was later than the relationship (r^2 = 0.68) developed for Horsham after Zadoks stage 33 but early enough to be used for potential mid-season N fertilizer recommendations. Additionally, ground-based hyperspectral data estimated plant N (g kg^{-1}) in Horsham with an r^2 = 0.86 but was confounded by water supply and N interactions. By combining canopy thermal and spectral properties, varying water and N status can potentially be identified eventually permitting targeted N applications to those parts of a field where N can be used most efficiently by the crop.

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Introduction

The ability to measure plant N and water status using reflected light has been well documented (Blackmer, Schepers, & Varvel, 1994; Gao, 1996; Osborne, Schepers, Francis, & Schlemmer, 2002; Peñuelas, Filella, Biel, Serrano, & Save, 1993). It is also well established that chemical and spectral characteristics of plants with nutrient deficiencies change when water stress is present (Peñuelas, Gamon, Fredeen, Merino, & Field, 1994; Pettigrew, 2004) masking and perhaps eliminating the specific spectral response of the deficiency. Hence, under field conditions with interacting water and N stresses, it is necessary to develop indices capable of determining the physiological status of the canopy to maximize the potential for response to management interventions. Response to applied N will be greater in areas where the plants are less water stressed. Indices providing simultaneous detection of N and water stress could prove useful for variable-rate management when applied to multi- or hyperspectral imagery, permitting spatial measures of these stresses.

Estimation of crop water status using thermal indices has been shown to be very robust (Clarke, 1997; Idso, Jackson, Pinter, Reginatio, & Hatfield, 1981; Jackson, Idso, Reginato, & Pinter, 1981; Moran, Clarke, Inoue, & Vidal, 1994) and could provide a means to map water status in a field. Since reflectance-based indices measure chemical and structural responses by plants they may not be as sensitive as thermal measures to the onset of water stress resulting from rapid stomatal closure and increased leaf temperature (Jackson, Pinter, Reginato, & Idso, 1986; Maracchi, Zipoli, Pinter, & Reginato, 1988). Optical measures can also be confounded by leaf angle changes due to wilting. By the time optical methods can detect changes, yield may already be affected.

For site-specific farming, it is important that canopy-level indices are developed and tested. Strong relationships have been shown between leaf chlorophyll concentrations and various remotely sensed indices (Carter & Spiering, 2002; Peñuelas et al., 1994). When scaled up to the canopy, where shadows (Fitzgerald, Pinter, Hunsaker, & Clarke, 2005), soil background (Huete, 1988) and structural differences (Moran, Pinter, Clothier, & Allen, 1989) are present, it may be more difficult to estimate leaf N status. The issue can be illustrated in the ‘‘cover problem’’ where an index may calculate the same value for an area of crop with low cover and high N concentration as in an area with high cover but low N. The amount of ‘‘green’’ detected by the sensors and then estimated by the index can be the same in both cases.

To estimate canopy-level N at varying amounts of canopy cover, different methods have been recently proposed. Daughtry, Walthall, Kim, De Colstoun, and Mcmurtrey (2000) used one multispectral index as a measure of cover and another as a measure of leaf chlorophyll to model leaf N at varying canopy cover. Similarly, Barnes, Clarke, and Richards (2000) developed the Canopy Chlorophyll Content Index (CCCI) based on planar domain principles (Clarke, Moran, Barnes, Pinter, & Qi, 2001). The CCCI uses two other indices derived from three spectral wavebands along the ‘‘red edge’’ part of a typical green plant spectrum to estimate cover and leaf N. Other measures of N status, based on hyperspectral data, have also been developed (Filella & Peñuelas, 1994; Fitzgerald et al., 2005; Strachan, Pattey, & Boisvert, 2002) but hyperspectral data are typically expensive and not widely available. The planar domain approach (Clarke et al., 2001) attempts to isolate the plant signal from the background using remotely sensed indices as surrogates for fractional cover and the property target (i.e., foliage temperature or plant N). The target index could be derived from hyperspectral or multispectral data but, here, two indices derived from multispectral and thermal data are presented for simultaneous measures of N and water status.

We postulate that by combining remotely sensed indices of canopy spectral and thermal properties that are cover independent, it is possible to target N inputs to areas with less water stress where the potential for response to in-season N application is high. We elaborate on the planar domain approach for measuring canopy N and water status with examples for wheat in an Australian rainfed region and a US irrigated system. We also include a hyperspectral measure of N status and discuss advantages and disadvantages between multi- and hyperspectral approaches to N detection under water-limiting conditions.

Theory

Derivation of foliage temperature

Based conceptually on work by Idso (1982) and described in Rodriguez, Sadras, Christensen, and Belford (2005b), the aggregate temperature of a given ground-acquired image or pixel containing a mixture of soil and plants (‘‘mixed’’ pixel) (T_m) depends on the fractional plant cover (f_c) and fraction of soil ($f_s = 1 - f_c$) and the temperature of each of these components. Theoretically, T_m and T_f will converge as the canopy approaches full cover (Fig. 1).

Hence, foliage temperature may be calculated as,

$$T_f = T_m - \Delta T(^\circ\mathrm{C}) \qquad (1)$$

where ΔT is the difference between T_m and T_f derived from direct foliage measurements or pixels identified as foliage in an image. The Normalized Difference Vegetation Index (NDVI), a remotely sensed index, can be used as a surrogate for canopy cover (Fitzgerald

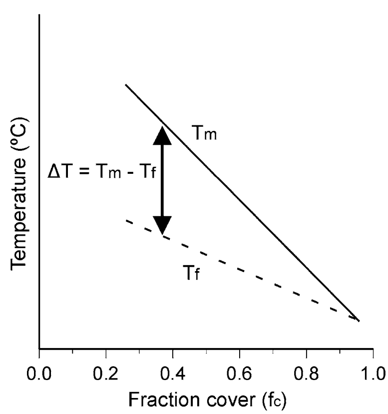


Fig. 1 Theoretical relationship between the mean temperature of mixed-pixels (T_m), foliage temperature (T_f), and fractional ground cover (f_c) (redrawn from Rodriguez et al., 2005b)

et al., 2005) and a relationship can be established between NDVI and ΔT. Once a relationship is developed between ΔT and NDVI (Rodriguez et al., 2005b), T_f can be solved from NDVI and thermal data.

This approach is very similar to work presented by Maas, Fitzgerald, and DeTar (2000) showing that T_m represents a mixed image or pixel such that,

$$T_m = f_c * T_f + (1 - f_c) * T_{si} \tag{2}$$

where, T_f = foliage temperature; f_c = fraction crop cover; $(1 - f_c) = f_s$ = fraction soil within the canopy; T_{si} = soil temperature inside the canopy.

Rearranging to solve for T_f:

$$T_f = [T_m - T_{si} * (1 - f_c)]/f_c \tag{3}$$

The authors used a remote sensing technique to estimate crop cover (f_c) (Maas, 1998, 2000) and developed a relationship between soil temperature within the canopy (T_{si}) and bare soil temperature from an area outside the canopy (T_{so}), allowing estimation of T_{si} and thus, T_f. The above is functionally equivalent to part of the ''empirical'' Vegetation Index Temperature trapezoid derived by Clarke (1997), although it aggregates the wet and dry soil terms and only requires that a pre-established relationship exist for T_{si} and T_{so}.

It should be noted that thermal sensors measure radiance, which has a non-linear relation to temperature described by the Stefan Boltzmann law where radiance is a function of T^4 (K). Thus, linear mixture analysis should be applied to radiance, not temperature. As such, Eq. 2 could be written:

$$T_m^4 = [f_c * T_f^4 + (1 - f_c) * T_{si}^4] \tag{4}$$

where, the temperature units are in K.

However, when leaf and soil temperature differences are small, such as shown here for winter wheat, the error between linear and non-linear estimation of foliage temperature is less then 0.5°C. As the temperatures of plant and soil components diverge, the error increases so linear mixture modelling should proceed with caution in hot, well-irrigated locations where soil and leaf temperature differences can be large.

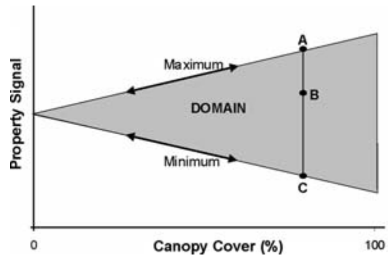
Derivation of the canopy chlorophyll content index (CCCI)

The Canopy Chlorophyll Content Index (CCCI) is derived from planar domain concepts (Clarke et al., 2001) and has been shown to relate to canopy chlorophyll and plant N in wheat and cotton (Barnes et al., 2000; Kostrzewski et al., 2002; Rodriguez, Fitzgerald, & Belford, 2006). The methodology is based conceptually on the Crop Water Stress Index (CWSI) discussed by Idso (1982) where boundary ranges in two-dimensions are set for two measures of interest and the index for any given point is calculated as the proportional distance between these boundaries (Fig. 2).

In the present study, the two measures of interest were canopy cover, represented by NDVI and a measure of chlorophyll or N status represented by the Normalized Difference Red Edge (NDRE). The NDRE takes the form of the NDVI but substitutes a band in the so-called ''red edge'' of a green leaf for the band measuring red light in the NDVI:

$$\mathrm{NDRE} = (790\,\mathrm{nm} - 720\,\mathrm{nm})/(790\,\mathrm{nm} + 720\,\mathrm{nm}) \tag{5}$$

Fig. 2 Derivation of an index using the using planar domain principles. The property signal in this case (Canopy Chlorophyll Content Index [CCCI]) is derived as: (B − C)/(A − C). (Modified from Clarke et al., 2001.)



where, 790 nm and 720 nm are narrow wavebands centred at these wavelengths.

The upper (maximum) and lower (minimum) boundaries encompassing the data (Fig. 2) can be derived by Eqs. 6 and 7. In practice, the boundaries are hand-drawn to encompass the range of data.

$$\mathrm{NDRE_{min}} = \mathrm{NDRE_{lowChl}} * f_c + \mathrm{NDRE_{soil}} * (1 - f_c) \tag{6}$$

$$\mathrm{NDRE_{max}} = \mathrm{NDRE_{highChl}} * f_c + \mathrm{NDRE_{soil}} * (1 - f_c) \tag{7}$$

where, $\mathrm{NDRE_{min}}$ = the lower Normalized Difference Red Edge (NDRE) boundary; $\mathrm{NDRE_{max}}$ = the upper Normalized Difference Red Edge (NDRE) boundary; $\mathrm{NDRE_{lowChl}}$ = an idealized crop canopy with very low chlorophyll concentrations; $\mathrm{NDRE_{highChl}}$ = an idealized crop canopy with high chlorophyll concentrations; $\mathrm{NDRE_{soil}}$ = measured soil values of NDRE.

Thus, the CCCI (Eq. 8) should allow estimation of N status at any time during the growing season, even with partial cover. Because of the maximum and minimum limits imposed between points A and C in Fig. 2, the CCCI has a range of 0–1 (low to high NRDE).

$$\mathrm{CCCI} = (\mathrm{NDRE} - \mathrm{NDRE_{min}})/(\mathrm{NDRE_{max}} - \mathrm{NDRE_{min}}) \tag{8}$$

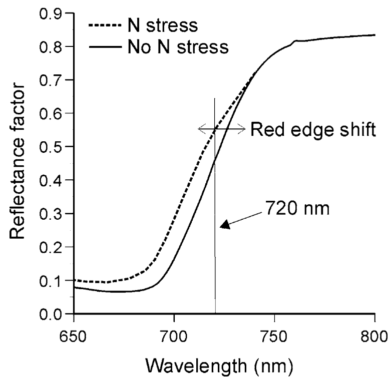
where, NDRE = the data point of interest (point b in Fig. 2).

The NDRE responds to changes in chlorophyll *a* (Chl *a*) due to the effect of Chl *a* on the shape of the spectral response curve along the red edge part of the spectrum (Fig. 3). For example, as Chl *a* concentration decreases, the absorption band centred near 670 nm increases in value, shifting the red edge to shorter wavelengths. Lower Chl *a* concentration therefore has the effect of increasing the reflectance value at 720 nm and decreasing the NDRE numerator while increasing the denominator. Thus, smaller values lie along the minimum line in Fig. 2 while larger NDRE values lie along the maximum line (Barnes et al., 2000).

Materials and methods

Data from two field sites are presented here for winter wheat: Horsham, Victoria, Australia and Maricopa, Arizona, United States. Some of the data from Horsham have been published previously (Rodriguez et al., 2006). These data are included here to allow direct comparison between Horsham and Maricopa and expand on the original sources, including the theoretical considerations above. Data from Maricopa have not appeared elsewhere.

Fig. 3 ''Red edge'' portion of a typical green leaf spectrum and the shift that occurs between N and non-N stressed leaves. The N stress spectrum is a slightly exaggerated idealized spectrum for illustrative purposes. The *y*-axis reflectance is a ratio of reflected energy from the target/reference so is unitless



Horsham

A field experiment near Horsham, Victoria, Australia (36.65° S, 142.10° W) was fully described in Rodriguez et al. (2005b) and salient features are presented here. Wheat (*Triticum aestivum* L., cv. Chara) was sown in a north–south direction on 17 Jun 2004 with a row spacing of 180 mm on a Horsham clay, a Grey Vertosol (Isbell, 1966). The aim was to develop canopies with a range of N and water stress conditions. In a split plot design with three replications, there were two main-plot irrigation levels (rainfed and decile 9 for local rainfall) and two plant densities (150 and 300 plants m^{-2}) nested in subplots with four levels of N (0, 16, 39 and 163 kg N ha^{-1}). A decile represents one 10% range of samples in a ranked population, such that a decile of 5 represents the point where half the data values are greater and half lower. In this case, the ranked population was the 30-year rainfall record. The irrigated plots were watered using an automatic sprinkler system whenever the accumulated rainfall deficit reached 20–50 mm from the decile 9 of seasonal rainfall in Horsham. Rainfall plus irrigation were 270 mm and 390 mm for the rainfed and irrigated treatments, corresponding to deciles 5 and 9 at Horsham, respectively. The subplots were 12 m × 18 m. Green canopy light interception was simultaneously recorded using a SunScan (Delta-T Devices Ltd, England). Agronomic dates and measurement periods are shown in Table 1. Measurements included above-ground biomass and total above-ground plant N content (g kg^{-1}). Air temperature, incoming solar radiation and relative humidity were recorded at 20 min intervals by a weather station installed at the experimental site.

A FieldSpec® Pro portable spectroradiometer (Analytical Spectral Devices, Boulder, CO, USA) measured light energy reflected from canopy and soil. It consisted of three detectors. One measured the visible/near infrared (VNIR) portion of the spectrum from 350 nm to 1050 nm wavelengths with a spectral resolution varying from 1.4 nm to 3 nm and two others measured the short-wave infrared (SWIR) from 900 nm to 2500 nm. The field of view (FOV) was 25 degrees for the sensor with unrestricted optics, as used here.

A ThermaCAM P40 (FLIR, Sweden) thermal infrared digital imager was used to measure emitted energy from canopy and soil. It was sensitive to energy in the spectral range of 7.5–13 μm. The FOV was 18° × 24° with an array of 240 × 320 pixels. Thermal data acquired on one date at Zadoks stage 60 (Zadoks, Chang, & Konzak, 1974) were analysed using the software ThermaCAM Reporter 7 Pro (FLIR, Sweden) to extract full canopy (T_m), soil (T_s) and foliage temperatures (T_f) (Rodriguez et al., 2005b).

Table 1 Dates and agronomic events in Horsham, 2004. DAE refers to days after emergence and DOY is Day of Year

Date	DOY	DAE	Zadoks	Activity
17 Jun	168	–	–	Planting
22 Jun	173	0	–	Emergence
12 Aug	224	51	14	Sampling 1
27 Aug	239	66	30	Sampling 2
20 Sep	263	90	33	Sampling 3
6 Oct	279	106	47	Sampling 4
18 Oct	291	118	55	Sampling 5
15 Dec	349	176	–	Harvest

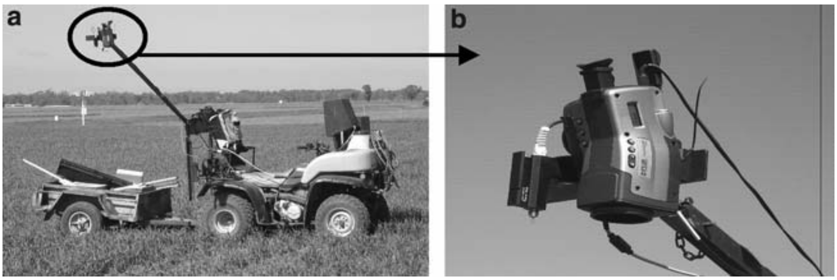


Fig. 4 (**a**) Instrument setup at Horsham. FieldSpec® Pro and ThermaCAM P40 mounted on a 4-wheel drive motorbike and (**b**) close-up image of the ThemaCAM P40 and the FieldSpec® Pro sensor in a pistol grip

The spectroradiometer and thermal imager were mounted on a 4 wheel-drive (4WD) motorbike (Fig. 4a). The sensor and imager were mounted on a steel boom 2.5 m above the soil surface pointing downwards at a 90° angle (Fig. 4b) to measure up-welling radiance and thermal emittance, respectively, from the wheat canopy. At the given height and FOV, the spectroradiometer yielded a sampling area of 0.93 m^2. The FOV of each was co-located so they viewed the same area.

Spectral calibrations for changing light conditions were carried out frequently using a 99% Spectralon panel (Labsphere, Inc., North Sutton, NH, USA). The dark current was automatically subtracted from the radiometric signal in each calibration session. Each radiometric data point represented a mean of 25 scans. The radiometric data were stored as relative reflectance in the range of 390–2500 nm. The spectral reflectance data were collected under clear sky conditions between 11:00 and 14:00 local time, which minimized the effect of changes in solar zenith angle. The 4WD motorbike was stopped for each measurement, which took about 5 min. Destructive plant samples were taken within the FOV of the FieldSpec® Pro after each measurement.

Maricopa

A hard red spring wheat (*Triticum aestivum* L., cv. Yecora Rojo) was sown into dry soil in a north–south orientation in a 2.5 ha field at the Maricopa Agricultural Center (33.073° N; 111.979° W, 350 m above sea level) in Central Arizona, USA in mid-Dec., 2003. The first post-plant irrigation was applied on 19 Dec 2003 (Day of Year [DOY] 353). Harvest occurred on 26 May 2004 (DOY 147). The soil is classified as a Casa Grande series with sandy loam to sandy clay loam textures (Post, Mack, Camp, & Sulliman, 1988).

The field was divided into 32 plots (each 11.2 by 20 m) separated from one another by irrigation border dikes. There were three plant densities and two fertilizer treatments that provided a wide range of canopy conditions in order to mimic those found in a producer's field. There were five rows m^{-1} and planting density treatments consisted of: Sparse (90 plants m^{-2}, single-line planting); Typical (164 plants m^{-2}, single-line planting); and Dense (291 plants m^{-2}, double-line planting). There were two fertilization levels, low N (93 kg N ha^{-1}) and high N (150 kg N ha^{-1}). The split application dates varied depending on irrigation scheduling since the fertilizer was applied in the irrigation water.

Canopy temperature was measured by walking transects across the central portion of each plot using a handheld Everest model 100.3Z infrared sensor (Everest Interscience, Tucson, AZ, USA). It was periodically calibrated to a blackbody of known temperature (Everest Interscience, Tucson, AZ, USA). This resulted in canopy-level temperatures representing mixed signals of soil and plant (T_m). Here, canopy is defined as the scale that includes plants, shadows and soil background in the FOV of the sensors. Foliage is defined as leaves only (with self-shadowing). Off-nadir measurements were also collected from the east and west sides of each plot with the sensor held at an angle of about 25° so that only foliage (T_f) was recorded by the sensor.

Spectral data were collected to calculate a normalized difference vegetation index (NDVI) and Crop Canopy Chlorophyll Index (CCCI) with an Exotech 100-BX handheld radiometer with a 15° field of view. The three bands had wavelength ranges of 650–675 nm, 715–725 nm, and 780–900 nm. This was referenced to a 99% Spectralon panel for calibration to reflectance. Only data collected on clear-sky days were analysed. Transects across each plot were walked with the sensor held in a nadir position at least twice weekly. Sensor data were collected at a constant 57° solar zenith. Meteorological data that included wet and dry bulb temperatures for calculation of vapor pressure deficit were collected with an on-site weather station. Cover was measured photographically with a digital camera by taking pictures of the same plot locations of two rows on a weekly basis. An area of approximately 2 m by 3 m was photographed from the camera held nadir to and 3 m above the crop.

An empirical relationship using a non-linear power fit was developed between Chl *a* concentration (μg cm^{-2}) and SPAD (Minolta Corporation, Ramsey, NJ, USA) readings by collecting leaf samples from all treatments for chlorophyll analysis on two dates (DOY 68 and 103). This relationship (r^2 = .96) was developed to convert the more easily measured field SPAD readings to Chl *a* concentration. The SPAD instrument is a hand-held meter that measures differential attenuation of transmitted light by leaves in wavebands centred at 650 nm and 940 nm. It has been found to be an excellent indicator of Chl *a* (Pinter et al., 1994). The third fully expanded leaf on the main stem was sampled from 12 plants per plot, one leaf per plant. One circular leaf punch of 6.85 mm diameter was removed from each leaf and two SPAD readings were taken per leaf. There were three replications per sample with 20 samples per date. The 12 leaves were divided into groups of six for Chl *a* and SPAD measurements to provide replication. SPAD readings were calibrated by measuring a ''checker'' of known SPAD value and normalizing all readings to this. Chl *a* concentration was determined using the 80% acetone-BHT method according to Lichtenthaler and Wellburn (1983). In the field, SPAD readings were acquired every 8–12 days from DOY 33–112 on the fully expanded upper leaf on 20 plants per plot in all plots.

Hyperspectral data analysis

In Horsham, hyperspectral data collected from five sampling dates (Table 1) from the FieldSpec Pro were analysed using principal component (PC) analysis and partial least square regression (PLS) with the multivariate analysis software, The Unscrambler®

(CAMO ASA Oslo, Norway). Independent of the measurement sessions and plant density, estimation of crop N content using the spectral response in the 450–1100 nm range was tested. This spectral range of 750 nm with 2-nm band width resulted in 325 spectral input variables. The output was reduced to nine PLS components, which were used to estimate plant N. All data were centred and a cross validation (leave one out) technique was used to validate the predictive model.

Results

Temperature

In Horsham, the theoretical relationship in Eq. (1) and Fig. 1 was tested using thermal images from each plot at Zadoks stage 60 (anthesis) on one date. The T_m is the mixed (mean) temperature for the whole image and T_f was measured in areas of the image unequivocally identified as foliage and represent a mean foliage value for the plot. The temperature of all pixels in these images decreased with increasing fraction of intercepted radiation, representing cover (f_c) (Fig. 5). Irrespective of N, irrigation or density treatments, the value of ΔT decreased with increasing cover. At f_c values greater than about 0.9 the mean image and foliage temperatures converged (Fig. 5).

In Maricopa, plot transects of ground-based temperature measurements were used as input for T_m and off-nadir measurements of foliage temperatures were used for T_f (Fig. 6a). The solid lines show line fits for DOY 57. These are extrapolated to indicate the expected fit of data for DOY 42 in Fig. 6b. Data from DOY 57 showed substantially the same relationship as that in Horsham (Fig. 5) with T_m and T_f converging at greater f_c, although f_c only ranged from about 0.65 to 0.90 (Fig. 6a). To test whether this was valid at lower fractional covers, data from another date (DOY 42) were included (Fig. 6a). Since actual temperatures varied on each date and the objective was to compare relative patterns between the two dates, T_m and T_f points from DOY 42 were offset to lie along the line for DOY 57 (Fig. 6b). This was done by adding a vertical (temperature) offset to the DOY 42, T_f data equal to the temperature difference at the mean f_c for DOY 42 and the projected line for DOY 57, T_f. This allowed the data to be compared in a relative manner to test whether they occupied the same data ranges (Fig. 6b).

The linear slopes (m) of T_f on DOY 42 (m = −4.0) and 57 (m = −5.5) (Fig. 6a) and the combined slope of these (m = −5.0) (Fig. 6b) were very similar. The slope of DOY 42, T_m

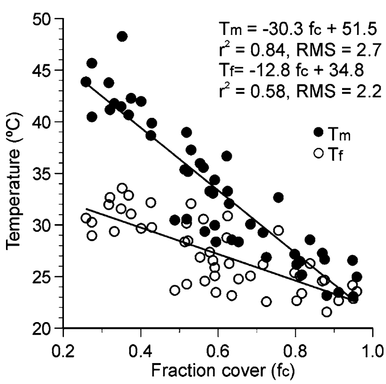


Fig. 5 Observed relationship between the mean temperature of every pixel in each plot canopy image (T_m), foliage temperature (T_f) and fractional cover (f_c) in Horsham. For each line there were 48 points with significance at α = .05 level (P < 0.001) (adapted from Rodriguez et al., 2005b)

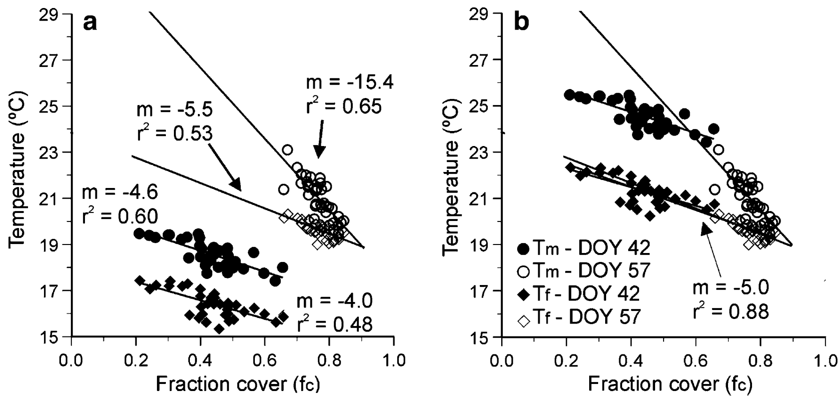


Fig. 6 Temperature versus fractional cover data from Maricopa, for two dates. T_m is mixed temperature for foliage + soil and T_f is the foliage temperature only. DOY is the Day of Year. (**a**) Temperature data not corrected to lie in the same data range. Solid lines show line fits for DOY 57. These are extrapolated to indicate the expected fit of data for DOY 42 in (**b**). (**b**) Offsets applied to match data ranges of DOY 42 and 57 but slopes were not changed from (**a**). The slope and r^2 values for the pooled DOY 42 and 57 for T_f data are displayed

measurements ($m = -4.6$) in Fig. 6a more closely resembles that of the T_f data. This can be explained by the variability in soil surface moisture across the plots on that day. This was due to a varying number of days since the previous irrigation and ground cover. At low cover, more of the wet soil surface would be exposed, biasing the T_m to lower values compared to a dry, and therefore warmer, soil. At high cover, the smaller amount of exposed soil would lead to less background influence and therefore lower temperatures at higher cover. Since the points on the line for DOY 42, T_m at higher f_c values had drier soil and there was less soil influence on the temperature, an offset was applied to match the DOY 57, T_m line rather than the mean as was done with the DOY 42, T_f line.

Canopy chlorophyll content index (CCCI)

In both Horsham and Maricopa, the NDRE versus NDVI plots showed a typical distinctive curvilinear shape (Figs. 7a, 8a). The data ranges were delineated visually with low plant N designated as the dashed line and high plant N delineated by the solid line in Figs. 7a and 8a. The CCCI is calculated using Eq. 8 for each point (Figs. 7b, 8b).

The r^2 was 0.68 for the relationship between CCCI and the N stress index (NS index) (Fig. 7b). The NS index is defined as shoot N per unit dry matter per area (Ng^{-1} dry matter m^{-2}) and is discussed in Rodriguez et al., 2006. The relationship held across N treatments irrespective of water stress intensity, for sampling dates 3–5 (Table 1). In Maricopa, r^2 was .53 for the CCCI and Chl *a* concentration measured between DOY 68–103 (after Zadoks 43) (Fig. 8b). The points below NDRE values of .10 are bare soil points not relevant to calculation of N status (Fig. 8a). Although not shown, early in the season, N (g kg^{-1}) in Horsham and the Chl *a* values in Maricopa were high while CCCI values were low so the CCCI was not able to account for early season N.

Hyperspectral nitrogen prediction, Horsham

Data from the ground-based hyperspectral sensor in the spectral range 450–1100 nm analyses using partial least square regression were unable to differentiate between

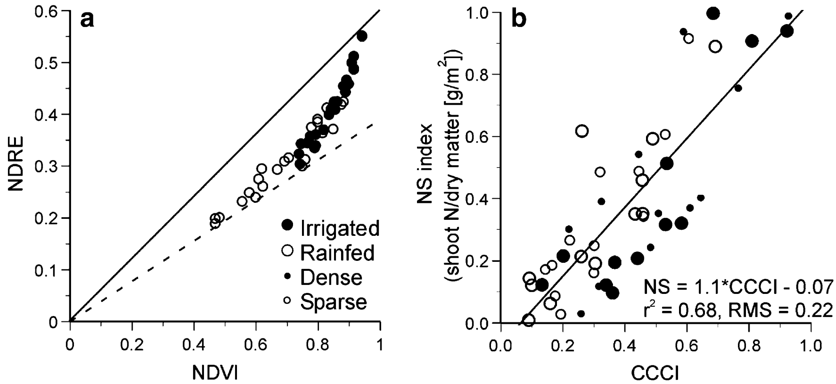


Fig. 7 (**a**) Relationship from Horsham between NDVI and NDRE for CCCI development (sampling dates 3–5, Zadoks 33–55). The solid and dashed lines are visually fit and represent the maximum and minimum values of NDRE. (**b**) The CCCI versus NS (nitrogen stress) index regression was significant at the $\alpha = 0.05$ level ($P < .001$) and represented 48 data points. Small and large circles show low and high canopy densities, and open and full circles indicate rainfed and irrigated treatments, respectively. After Rodriguez et al. (2006)

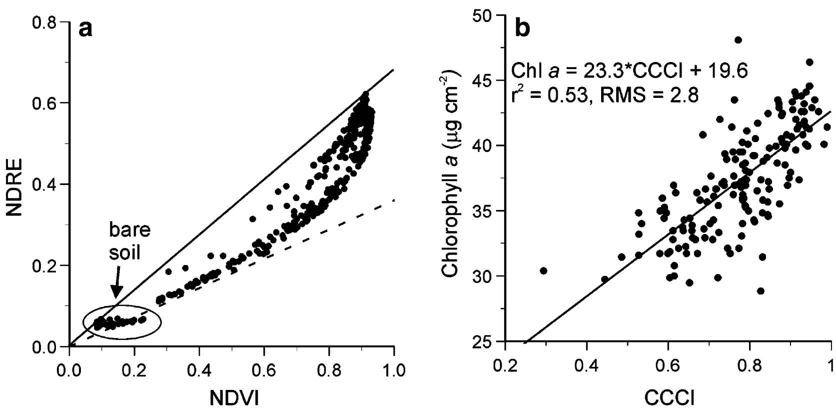


Fig. 8 (**a**) Relationship from Maricopa between NDVI and NDRE for CCCI development (DOY 33–112). The solid and dashed lines are visually fit and represent the maximum and minimum values of NDRE. (**b**) CCCI and leaf chlorophyll *a* for DOY 68–103 ($P \leq .0001$, $n = 160$). NDRE values below about .1 represent bare soil

irrigated, low N treatments and rainfed, high N treatments. So, rainfed treatments were removed from further analysis. An equation was developed to predict canopy N content in non-water stressed treatments for all five measurement dates across all N and plant density levels. It was possible to estimate N content with a root mean square error of prediction (RMSEP) of 0.66 using nine partial least square components (Fig. 9), reducing the data from 325 spectral input variables. The cross-validated linear regression explained 86% of the observed variation.

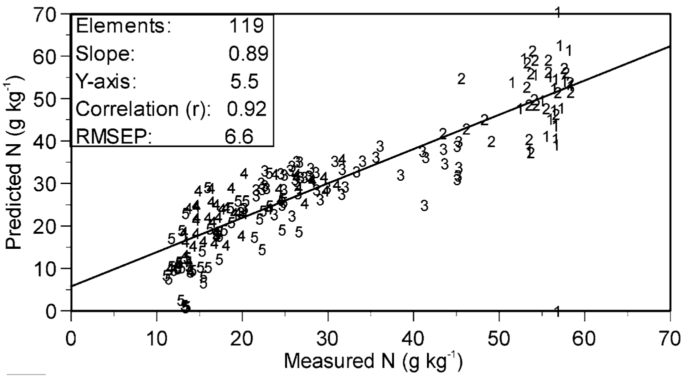


Fig. 9 Measured versus predicted N using partial least square regression with hyperspectral data for the irrigated plots. The numbers 1–5 correspond to sampling dates 1–5, where 1 was the earliest growth stage and 5, the oldest

Discussion

Plant temperature has long been recognized as having potential to determine the water status of crops (Idso, 1982; Jackson et al., 1981). For rainfed agroecosystems such as those in Australia, seasonal rainfall is the main determinant of crop growth, response to in-crop N applications and final grain yield. In addition, plant water availability can vary spatially across the landscape by soil type, the presence of subsoil salinity (Rodriguez, Nuttall, Sadras, Rees, & Armstrong, 2005a), soil strength (Sadras, O'Leary, & Roget, 2005) and root diseases. In highly spatially variable environments, precision agriculture and variable rate technologies are being considered as solutions to increase crop profitability, reduce seasonal uncertainty and minimize unwanted losses of water and nutrients from the production system.

For remote imagery to be useful, the fewest number of ground parameters must be acquired and T_f cannot be practically measured during aerial overpasses of a sensor. Because of meteorological variations (humidity, wind speed, etc.) and the mixed pixel problem, T_f is the most difficult temperature parameter to measure remotely. The methods presented in Rodriguez et al. (2005b) and extended here allow derivation of T_f based on established relationships either between the ΔT ($T_m - T_f$) and cover or soil temperature outside the field (T_{so}) and soil temperature inside the crop (T_{si}) (Maas et al., 2000). Assuming one of these relationships is established, T_f can be determined and used as input to water stress indices (Idso, 1982; Moran et al., 1994), which are fundamentally based on foliage – air temperature ($T_f - T_a$). This relationship can then be applied to thermal imagery to develop relative stress maps (Clarke, 1997) or a Crop Stress Index (CSI) as presented by Rodriguez et al. (2005b).

The CSI is not a calibrated measure such as the Crop Water Stress Index (Idso et al., 1981; Idso, 1982; Jackson et al., 1981) or the Water Deficit Index (Moran et al., 1994). Calibrated measures of stress include maximum and minimum temperatures for $T_f - T_a$ from derived stressed and unstressed baselines, allowing for temporal comparisons as the stress develops. Therefore the CSI represents an instantaneous indication of the relative spatial variation in ''crop stress'' or its physiological status, indicative of water stress or any other stressors that cause the plants to close their stomata (Jackson et al., 1986) and that most likely will limit the response of the crop to additional tactical N applications. If the objective of a study is to measure stress across different acquisition times and dates, then the Crop Water Stress Index or Water Deficit Index approach needs to be used. The CSI is useful due to the few inputs needed to derive a stress index and its simple implementation to thermal imagery, potentially allowing producers rapid access to maps that can be used for field scouting.

The mixed-pixel temperature (T_m) measurement requires a dry soil background since it assumes that the soil plus plant mixed-pixel will converge with foliage temperature near $f_c = 1$ (Figs. 1, 5). With variably wet soil backgrounds, this may not occur and a different type of relationship, which may be non-linear or skewed, is possible. The slope of the DOY 42, T_m data set does not converge with DOY 42, T_f (Fig. 6a) and differs from that of DOY 57, T_m (Fig. 6b) because soil moisture varied between plots causing different temperature relationships with cover. Thus, this method should be applied only under dry surface conditions. Rainfall-dominated regions of the Midwestern United States or central eastern and northeastern Australia are examples of important wheat growing regions. Given the episodic rainfed patterns present in the Australian Victoria region (and in other parts of the world) where soil surfaces are often dry, this should not limit the approach. In Maricopa, where wheat is irrigated, this approach could be useful for irrigation timing or targeting locations in a field where stress is developing for spatially variable irrigation. In these irrigated systems, knowing when to irrigate is only important sometime after the previous irrigation, when the soil surface has dried, typically after about 10 days. Thus, the soil surface is usually dry when irrigation forecasting would occur.

Canopy chlorophyll content index (CCCI)

In Arizona, split applications of N are a common management practice. Ideally these occur based on crop phenology but typically N will be applied based on days since the previous fertilization. For example, in the present study, N applications were made on approximately DOY 35, 56, 75 and 87 although there was a range of a few days around each DOY depending on irrigation date. By DOY 68 (Zadoks 43), the CCCI was able to definitively estimate Chl *a*. Thus, the CCCI would have been able to estimate Chl *a* concentrations by the middle of the season, capturing the last two dates. In Horsham, the index was able to capture plant N by Zadoks 33 (sampling date 3), also early enough to provide information for tactical N management decisions. A further research issue would be to develop thresholds for N content or Chl *a* for N input recommendations.

Creating the CCCI requires a seasonal data set that can provide coefficients for the upper and lower NDVI versus NDRE boundaries. Research is needed to determine if these are stable across years although preliminary data (unpublished) suggest this to be the case. If this holds true then the CCCI can be calculated from stable baselines established in previous years for a given region or crop variety. Another requirement for current application of the CCCI is radiometric calibration for the NDVI and NDRE indices. It would be possible to mount a calibration reference panel on ground-based equipment (i.e., tractors) to correct for changing sky conditions. This would be more problematic for aerial acquisition of images since deploying large radiometrically stable targets is not realistic at the field scale. This issue is not unique to the CCCI and is relevant to any remote index attempting to quantify changes over time and warrants further research for practical applications.

It has not yet been determined what the effect of soil background color or shadows is on the CCCI. In Horsham, the soil backgrounds were dry during measurement sessions. In Maricopa, soil backgrounds varied from moist to dry. This did not seem to influence the

CCCI but, by DOY 68, when the relationship with Chl *a* was significant, cover was nearly complete. The spectral data were acquired at a constant solar zenith so sun angle differences, per se, did not affect the data. However, since the crop developed during the measurement period, shadows became more complex during the season. Changes in soil background, amount of shadows and canopy structure added to variability of the measurements before canopy closure.

Combining information in the reflected light and emitted thermal regions of the spectrum could allow a new type of management option for producers—targeted application of inputs based on the crop potential for utilization. Assuming that reliable indices can be developed for crop N (or other factors) and water status, maps of regions within a field that will be more responsive to a management input can be produced. These data could then be input to variable rate equipment to target locations of optimal response for the input, potentially reducing cost and impact to the environment due to off-site movement of chemical, such as N into surface and ground waters.

Hyperspectral N estimation

In Horsham, hyperspectral measurements and the PLS data reduction technique successfully estimated early season N (from Zadoks 14), whereas the CCCI could only estimate N after Zadoks 33. However, the CCCI was able to estimate N under low water conditions in Horsham whereas the hyperspectral approach was confounded. It is currently not known how stable the hyperspectral relationship is and whether the regression coefficients can be generalized. More research is needed before it is can be determined whether a multispectral or hyperspectral approach is superior for robust N status detection under low water conditions.

Conclusion

It is possible to identify areas of relative stress in producer's fields due to water or other factors that affect stomatal closure using thermal imaging technologies. In rainfed conditions, this can be used to identify areas having potential for crop response to additional N inputs. If combined with maps of crop N status, this technology could allow targeted applications of N into those areas of higher potential response. Further research should attempt to improve the relationships between N status and CCCI as well as test the derivation of T_f more fully under various cropping systems and conditions. Under irrigated systems, these methods could help target irrigation scheduling and N input timing. Full implementation of a management scheme would additionally require quick image and ancillary data processing and delivery to the producer as well as the ability to apply variable rate N to the identified areas in a timely manner. Overall, the combination of thermal and spectral information has the potential to improve in-season management under spatially variable water and N stress conditions found in rainfed fields or just prior to an irrigation cycle in irrigated crops.

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